
“Uncovering the time-varying relationship between commonality in liquidity and volatility”

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Abstract

This study examines the dynamic linkages between commonality in liquidity in international stock markets and market volatility. Using a recently proposed liquidity measure as input in a variance decomposition exercise, we show that innovations to liquidity in most markets are induced predominately by inter-market innovations. We also find that commonality in liquidity peaks immediately after large market downturns, coinciding with periods of crisis. The results from a dynamic Granger causality test indicate that the relationship between commonality in liquidity and market volatility is bi-directional and time-varying. We show that while volatility Granger-causes commonality in liquidity throughout the entire sample period, market volatility is enhanced by commonality in liquidity only in sub-periods. Our results are helpful for practitioners and policy makers.

JEL classification: C10, C32, G01, G15

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1. Introduction

Commonality in liquidity can be defined as the co-movement in liquidity among individual stocks (Karolyi et al., 2012). Here, we offer solid, novel empirical evidence of the causal relationship between global commonality in liquidity in international stock markets and global market volatility and we show that this relationship is time-varying and that it displays feedback effects during episodes of crisis. Unlike the scarce extant literature studying commonality in liquidity around the world (i.e. Brockman et al., 2009 and Karolyi et al., 2012), we propose measuring commonality in liquidity *dynamically*. To do so, we construct systemic liquidity measures based on individual stocks for every market in a sample of nine mature markets,¹ following a recently proposed market liquidity indicator developed by Abdi and Ranaldo (2017). We then use these country-specific liquidity measures as inputs in a variance decomposition exercise, which allows us to break down the total variation in liquidity for each market into its own liquidity shocks and foreign-market liquidity shocks. We estimate a global commonality index that reflects liquidity spillovers across these nine major stock markets and which, in line with Diebold and Yilmaz (2012), is constructed as the sum of cross-variance shares in liquidity for all markets in our sample. Next, we relate our commonality index to a measure of aggregate global market volatility using data for the same markets. To carry out this step, we use a dynamic Granger causality test, as proposed by Hurn et al. (2016), that allows us to detect directional causality in a time-varying fashion between commonality and market volatility.

Several novel, significant insights can be drawn from our main results. First, we show that the relationship between commonality in liquidity and market volatility is complex and time-varying. That is, we document that volatility Granger-causes commonality in liquidity throughout the entire sample period. This is consistent with theoretical models, including, for example, that developed by Brunnermeier and Pedersen (2009). In this framework, high market volatility leads to an increase in commonality as a consequence of a reduction in the provision of liquidity available for all financial intermediaries. Second, for the first time, we are able to document that commonality in liquidity also Granger-causes volatility, and that this occurred in the aftermath of the Global Financial Crisis, coinciding with high levels of uncertainty in European bond markets. This finding might be interpreted as evidence of the existence of adverse loop effects in which shocks to stock market liquidity

¹ We consider the market capitalization of NASDAQ, NYSE, EURONEXT, Deutsche Boerse AG, Six Swiss Exchange, LSE, BME, TMX Group and Japan Exchange Group Inc., which represents 67.3% of total world stock market capitalization, as reported by the World Federation of Exchanges in December 2018.

endogenously cause stock market volatility and vice versa. Such a feedback effect sheds new light on the endogenous nature of financial shocks arising during crisis episodes, which we show are aggravated by liquidity considerations.

In addition to the main finding outlined above, we also show (as expected) that global commonality in liquidity peaks during episodes of market turmoil and that it remains at very high levels even after peaks in market liquidity have fallen. Indeed, we document high levels of commonality in liquidity from the beginning to the end of the subprime crisis. Global commonality remains high even when market specific liquidity measures have returned to their pre-crisis levels. Finally, as a side product of our analysis, we show that the measure proposed by Abdi and Rinaldo (2017) performs very well when measuring liquidity in several international stock markets, in the sense that it provides sensible results consistent with our knowledge of these markets and their dynamics between July 2000 and December 2016.

Market liquidity is the ability to trade large quantities of an asset without depressing its equilibrium price and, as such, it constitutes a crucial feature of any financial asset. It is of great importance for an investor's portfolio choices and policy considerations. In recent decades, empirical studies have shown that stock returns carry a premium for liquidity (see Amihud and Mendelson, 1986; Eleswarapu and Reinganum, 1993; Brennan and Subrahmanyam, 1996; Datar et al., 1998; Amihud, 2002).² Studies by Chordia et al. (2000), Amihud (2002), Hasbrouck and Seppi (2001) and Huberman and Halka (2001) find that the level of liquidity co-moves among similar stocks and across time, while studies by Acharya and Pedersen (2005), Holmstrom and Tirole (2001) and Pastor and Stambaugh (2003) show that stocks are exposed to a systemic (market-wide) level of liquidity. As such, liquidity and commonality among financial assets are a first-order consideration in the decision-making process of investors and market makers, and in the designing of optimal policy frameworks by regulators.

Commonality in liquidity can be traced back to common variation in either demand or supply of liquidity. Demand-generated commonality can be attributed to correlated trading behavior (Chordia et al., 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001). In this branch of the literature, the claim is made that large trading orders across a wide range

² Amihud and Mendelson (1986) were the pioneers in bridging market microstructure and asset pricing. Eleswarapu and Reinganum (1993) examined the seasonality effects of this same measure, while Brennan and Subrahmanyam (1996) incorporated it into a Fama-French factors framework. Using the turnover rate, research by Datar et al. (1998) and Brennan et al. (1998) further examined the role of liquidity for stock returns.

of markets put significant pressure on the inventory of dealers, inducing variation in inventory levels and leading to co-movements in the level of liquidity. Studies by Kamara et al. (2008) and Koch et al. (2016) stress the steadily increasing importance of institutional investors and their index-related trading as a source of demand-oriented co-movements in liquidity. The latter authors find that stocks held by mutual funds, traded in similar time patterns, experience larger trade imbalances and, hence, give rise to commonality in liquidity. Supply-generated commonality in liquidity, on the other hand, can be related to funding constraints in the provision of liquidity by financial intermediaries. Studies by Coughenour and Saad (2004) and Hammed et al. (2010) report a rise in liquidity commonality within industries, when returns in other industries are large and negative. Furthermore, they argue that this phenomenon of spillovers in the level of illiquidity in industries is partial proof of commonality as the dry-up in funding liquidity affects all stocks.

Empirical evidence of commonality in liquidity focuses primarily on the U.S. financial markets. To the best of our knowledge, the only relevant exceptions are the studies by Brockman et al. (2009) and Karolyi et al. (2012). Brockman et al. (2009) investigate the extent to which commonality is a global vs. local phenomenon and identify the sources of commonality both within and across countries. Karolyi et al. (2012) examine commonality in liquidity in 40 countries and link global commonality to a variety of capital market conditions. Their study provides a comprehensive view of liquidity commonality and its intra-market determinants across time and countries. Yet, the literature to date has not provided reliable empirics that can shed light on the dynamic nature of the relationship between commonality in liquidity and market volatility.

Here, we measure global commonality in a dynamic fashion, which enables us to link it dynamically with market volatility and to show the strong bidirectional causality between the two, especially in crisis periods and their aftermath. Our methods also allow us to clearly decompose intra- and inter-market spillover effects and their relative strengths. We find that three-quarters of the variation in market liquidity depends on foreign market liquidity shocks, which provides a more cross-market oriented explanation of commonality.

The rest of this paper is organized as follows: Section 2 lays out the methodology used in our analysis. Section 3 describes the data. Section 4 discusses the empirical results and, finally, Section 5 concludes.

2. Methodology

We divide our empirical investigation into three sections. First, we calculate commonality in liquidity for each of the nine stock markets in our sample, using the bid-ask spread proposed by Abdi and Rinaldo (2017). We then estimate global commonality in liquidity, following Diebold and Yilmaz (2012). Finally, we use the new time-varying Granger causality test, as developed by Hurn et al. (2016), to investigate the dynamic causality between commonality in liquidity and market volatility.

2.1. Systemic Liquidity

To measure systemic liquidity risk, we follow a recently proposed estimator for market liquidity, as developed by Abdi and Rinaldo (2017). Their method is based on close, high and low prices and bridges the well-established bid-ask spread formulated by Roll (1984) and the more recent High-Low (HL) spread developed by Corwin and Schultz (2012). This measure has several advantages over competing alternatives. For example, compared to other low-frequency estimates, this method uses wider information (i.e. close, high, and low prices), it provides the highest cross-sectional and average time-series correlations with the TAQ effective spread, and it delivers the most accurate estimates for less liquid stocks.

Abdi and Rinaldo's (2017) measure is based on the same theoretical assumptions as those made for the spread modelled by Roll (1984). The effective spread s is estimated as

$$s = 2\sqrt{E(c_t - \eta_t)(c_t - \eta_{t+1})} \quad (1)$$

where c_t represents the daily observed close log-price, and η_t refers to the mid-range, defined as the mean of daily high and low log-prices. Although this closed-form solution of the bid-ask spread measure is similar to Roll's (1984) autocovariance measure, it builds on the covariance of consecutive close-to-midrange prices rather than on close-to-close prices.

Owing to errors in the estimation procedure, some estimates of equation (1) are negative. Following Corwin and Schultz (2012), Abdi and Rinaldo (2017) propose two versions of the spread. In the first – known as the *two-day corrected* version – negative two-day estimates are set to zero and then the average of the two-day calculated spreads is taken. In the second – known as the *monthly corrected* version – negative monthly estimates are set to zero. Equations (2) and (3) show how the spreads are calculated:

$$s_{two\ day\ corrected} = \frac{1}{N} \sum_{t=1}^N \widehat{s}_t, \quad \widehat{s}_t = \sqrt{\max\{4(c_t - \eta_t)(c_t - \eta_{t+1}), 0\}} \quad (2)$$

$$\widehat{s_{monthly\ corrected}} = \sqrt{\max\left\{4\frac{1}{N}\sum_{t=1}^N(c_t - \eta_t)(c_t - \eta_{t+1}), 0\right\}} \quad (3)$$

where N is the number of trading days in a month. Finally, we calculate a monthly country-specific systemic liquidity measure as the equally weighted average of the monthly spread of individual stocks.

2.2 Global commonality in liquidity

Our approach to estimating commonality in liquidity is based on the methodology introduced by Diebold and Yilmaz (2012), which builds on the seminal work on VAR models by Sim (1980) and the notion of variance decomposition. The starting point for the analysis is the following VAR(p):

$$x_t = \sum_{i=1}^p \Phi_i x_{t-i} + \varepsilon_t \quad (4)$$

where $x_t = (x_{1t}, x_{2t}, \dots, x_{Kt})$ is a vector of K endogenous variables, Φ_i is a $K \times K$ matrix of parameters to be estimated, and ε_t is a vector of disturbances that has the property of being independently and identically distributed (i.i.d.) over time, $t = 1, \dots, T$, with zero mean and Σ is a covariance matrix. If the VAR model is covariance stationary, we can derive the moving average representation of model (5), which is given by

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \quad (5)$$

where $A_i = (\Phi_1 A_{i-1} + \Phi_2 A_{i-2}, \dots, \Phi_p A_{i-p})$, A_0 is the $K \times K$ identity matrix and $A_i = 0$ for $i < 0$. Variance decomposition allows us to break down the h-step ahead forecast error variance into *own variance shares*, the fraction of the forecast error variance in forecasting y_i due to shocks to y_i , for $i=1, 2, \dots, N$, and cross variance shares, or spillovers, the fraction of the forecast error variance in forecasting y_i due to shocks to y_j for $j=1, 2, \dots, N$ and $j \neq i$.

Diebold and Yilmaz (2009) proposed using Cholesky decomposition to break down the variance. However, Cholesky decomposition is sensitive to ordering. Diebold and Yilmaz (2012) resolve this ordering problem by exploiting the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), in which variance decomposition is invariant to the ordering of the variables. Variable j 's contribution to i 's h -step ahead generalized forecast error variance decomposition is given by:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \quad (6)$$

where Σ is defined as the covariance matrix of the error vector ε , σ_{ij} is the (estimated) standard deviation of the error term for the variable j , and e_i is a selection vector with a value of one on the i -th element and zero otherwise. The sum of contributions to the variance of the forecast error of each market do not necessarily add up to one; thus, we normalize each entry of the variance decomposition matrix as

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^N \theta_{ij}(H)} \quad (7)$$

where $\sum_{j=1}^N \tilde{\theta}_{ij}(H) = 1$ and $\sum_{i,j=1}^N \tilde{\theta}_{ij}(H) = N$.

This normalization enables us to construct the following volatility spillover measures:

- The *total spillover index* which measures the contribution of spillovers of shocks across all markets to the total forecast error variance:

$$TS(H) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}(H)} \cdot 100 \quad (8)$$

- The *directional spillovers* received by market i from all other markets j :

$$DS_{i \leftarrow j}(H) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}(H)} \cdot 100 \quad (9)$$

- The *directional spillovers* transmitted by market i to all other markets j :

$$DS_{i \rightarrow j}(H) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}(H)} \cdot 100 \quad (10)$$

- The *net spillover*, namely the difference between the gross shocks transmitted to and the gross shocks received from all other markets, which identifies whether a market

is a receiver/transmitter of shocks from/to the rest of the markets being examined. The net spillover index from market i to all other markets j is obtained by subtracting equation (9) from equation (10):

$$NS_i(H) = DS_{i \rightarrow j}(H) - DS_{i \leftarrow j}(H) \quad (11)$$

2.3. Global Market Volatility

Our measure of volatility is based on the traditional realized volatility (RV) estimator, as explained, for example, in Andersen and Todorov (2010). This has been shown to be a useful methodology for estimating and forecasting conditional variances for risk management and asset pricing.³ The RV estimator can be expressed as:

$$RV_{\text{monthly}} = \sqrt{\sum_{t=1}^N r_t^2} \quad (12)$$

where r_t are the log returns and N is the number of trading days per month. In order to examine the time-varying relationship between commonality in liquidity in international stock markets and market volatility, we need to aggregate individual volatilities and, to do so, we employ principal component analysis, taking the first component as our measure of global market volatility.

2.4. Dynamic Granger Causality

To analyze the dynamic relationship between commonality in liquidity in international stock markets and global market volatility, we follow the methodology proposed by Hurn et al. (2016). While emphasizing that the Granger causality test is highly sensitive to the time horizon of its estimation, they propose considering time dynamics to detect periods of instability in the causal relationship. The method proposed is based on an intensive recursive calculation of Wald test statistics for all sub-samples in a backward-looking manner in which the final observation of all samples is the (current) observation of interest. Inferences regarding the presence of Granger causality for this observation rely on the supremum taken over the values of all the test statistics in the entire recursion. As the sample period moves forward, all subsamples move forward and the calculation rolls ahead in a changing rolling window framework – hence its name, ‘recursive rolling algorithm’. The estimation procedure is based on a VAR model framework in which the selection of

³ See Liu et al. (2015) and references therein.

the lag order is obtained using the Bayesian Information Criterion (BIC). As in Hurn et al. (2016), the 5% critical value sequences over time are obtained through bootstrapping with 500 replications.

3. Data

We collect daily close, high and low prices, for the period July 2000 through to December 2016, for the following markets (Canada, Germany, France, Italy, Japan, Spain, Switzerland, the U.K. and the U.S.).⁴ We confine our sample of stocks to those listed in the country's specific major stock market index. To obtain a measure of market-wide liquidity in each stock market, we first calculate the daily spreads of our restricted set of stocks defined above and aggregate them on a monthly basis. Then, we sum the monthly stock-specific spreads and weight them equally by the number of stocks in each market so as to obtain a monthly market-wide aggregate spread for each market.

The number of stocks in each index is subject to fluctuations over the entire sample period. This reflects the fact that some firms have gone public after the sample start date while others have recently been delisted for reasons of financial restructuring or the merging of business activities. We control for these possibilities by adjusting the weighting over time. In compliance with the screening principles proposed by Karolyi et al. (2012), we aim to obtain a broad range of stocks within each country while avoiding any differences in trading behavior or conventions. In keeping with this objective, we also exclude depositary receipts (DRs), real estate investment trusts (REITs), investment funds and preferred stocks from our sampling. Moreover, we exclude stocks with price data for less than 24 months, although this is rarely applicable. The monthly spread estimates for U.S. stocks are taken from Angelo Rinaldo's website.⁵ All other daily price data for stocks are extracted from Datastream. Our final sample of stocks outside of the U.S. consists of 505 stocks from eight different countries.

4. Results

In this section we report our empirical results. We first provide the reader with insights into the dynamics of market liquidity for selected countries. Then, we present our measure of

⁴ The sample includes seven of the world's advanced economies (G7).

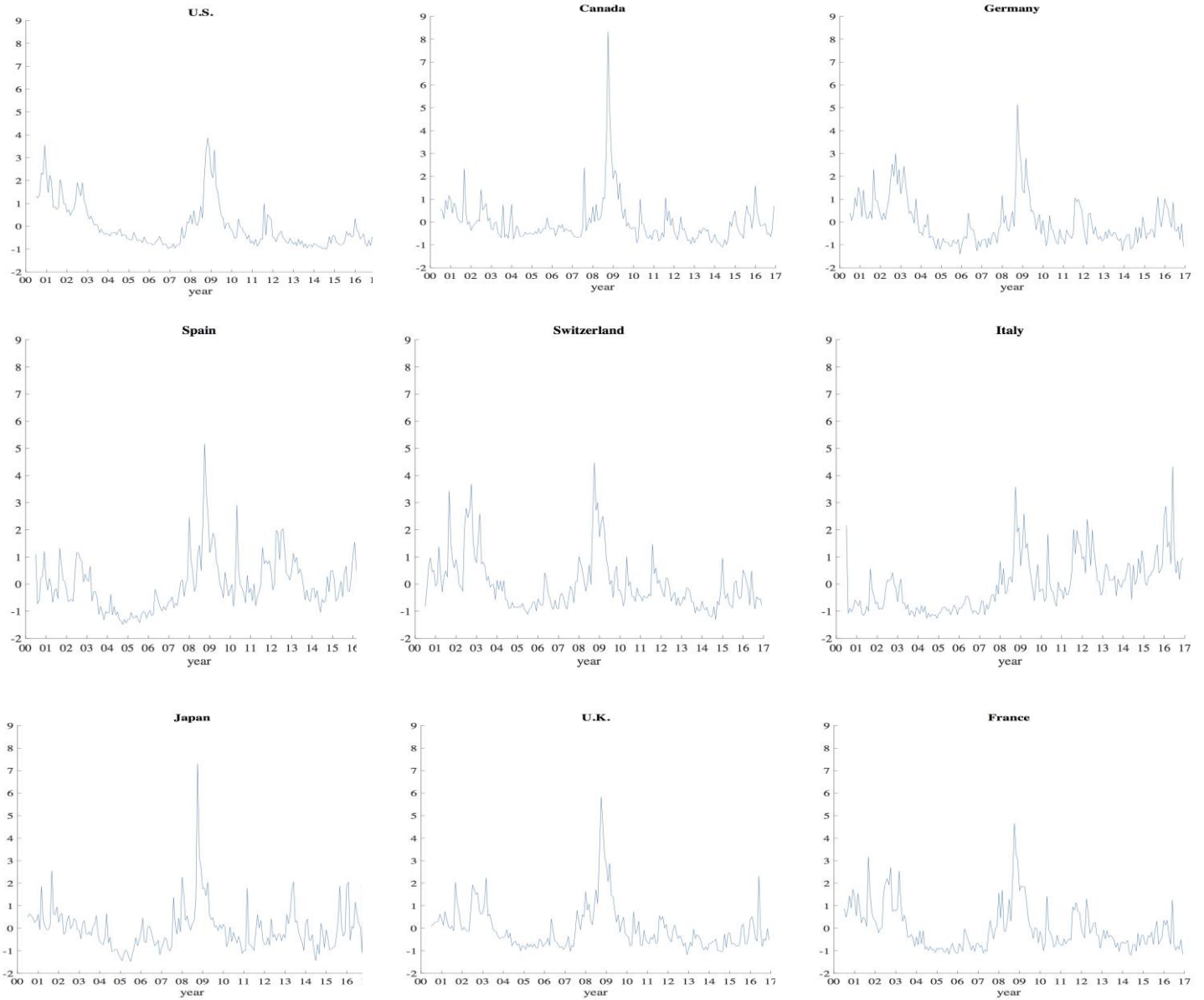
⁵ https://sbf.unisg.ch/en/lehrstuehle/lehrstuhl_rinaldo/homepage_rinaldo/research-material

global commonality in liquidity. Finally, we describe the time-varying relationship between global commonality in liquidity and aggregate market volatility.

4.1 Liquidity Measure

Figure 1 shows the estimated market liquidity for each country in our sample. An increase in the spread is associated with a higher level of illiquidity in the respective stock market. We observe that market liquidity is substantially higher in some periods than in others and tends to decrease during financial crises. For example, market illiquidity was high in the U.S., Switzerland, Germany and France during the dot-com bubble. Likewise, for all countries, illiquidity dramatically increased during the financial crisis of 2008-2009. It is also noteworthy that Italy exhibited higher illiquidity than the rest of the countries between 2011-2017. Table A1 shows the descriptive statistics of market systemic liquidity for each country. Our results show that market illiquidity was higher and more volatile during the financial crisis (2008-2009) than before or after it. The U.S., Canada, Germany and Japan are the countries with the lowest levels of market liquidity during this sub-period. Interestingly, the mean and the standard deviation during the post-crisis period are lower than during the pre-crisis period (except for the peripheral countries in our sample, Italy and Spain, due to the European Sovereign debt crisis).

Figure 1: Dynamics of market wide liquidity



Note: Time-series variation in market liquidity for select countries. Monthly country-specific liquidity measures are calculated as the equally weighted average of the monthly spread of individual stocks. The sample runs from July 2000 to December 2016. For illustrative purposes, the liquidity measures in the plots are standardized.

4.2 Global commonality in liquidity

Table 1 shows the estimation results for the full-sample spillover analysis based on a 6-month-ahead forecast error variance decomposition. Element $ijth$ of the matrix represents the contribution to the forecast error variance of market i from shocks to market j . The diagonal elements display the intra-market spillovers, where $(i = j)$. The off-diagonal

elements of the matrix show the cross-market spillovers. The row sums (labelled “From others”) represent the total spillovers received by the respective market as denoted in this particular row, whereas the column sums (labelled “To others”) represent the sum of spillovers transmitted by market i in the respective column. The difference between the column and the row sum represents the net spillover. It describes whether the respective market has transmitted (received) more shocks to (from) all of its counterparts. Finally, the total spillover statistic, shown in the bottom-right corner, indicates the degree of interconnection between the system of variables, i.e. our measures of systemic market liquidity.

Table 1. Global commonality in liquidity

	US	CA	GER	SP	SWI	IT	JP	UK	FR	From others
US	18.82	15.53	13.02	8.47	9.40	5.61	4.58	11.73	12.79	81.17
CA	10.40	25.06	11.48	8.27	7.51	7.18	7.38	13.26	9.43	74.92
GER	10.32	10.77	18.86	8.95	11.92	7.90	5.45	12.31	13.48	81.13
SP	8.34	9.92	11.30	16.96	9.27	12.94	5.60	12.37	13.25	83.03
SWI	9.58	9.99	15.15	9.67	16.14	7.50	4.24	13.53	14.17	83.85
IT	7.19	10.23	11.43	14.03	8.16	20.20	5.52	11.98	11.22	79.79
JP	7.19	13.16	12.81	9.46	7.69	7.41	21.42	11.77	9.04	78.57
UK	8.60	12.88	13.06	10.95	10.16	9.03	5.37	17.39	12.51	82.60
FR	10.35	9.99	14.57	11.39	11.71	8.27	4.34	12.90	16.43	83.56
To Others	90.82	117.58	121.71	98.19	92.00	86.09	63.94	117.28	112.37	Total Spillover =
Net cont. (to-from)	9.65	42.64	40.57	15.15	8.15	6.30	-14.63	34.67	28.80	80.96

Note: Columns show the market producing the shock and rows the market receiving the shock. The diagonal elements represent intra-market spillovers while the off-diagonal elements represent the pairwise liquidity directional spillovers. The table shows the 6-month ahead forecast error variance decomposition, based on a VAR model with a lag length of 2, following the Akaike’s information criterion (AIC).

As can be observed, the inter-market spillovers are higher than the intra-market spillovers, since both the column *from others* and the row *to others* display higher figures than those on the diagonal. This means that variation in market-wide liquidity depends mainly on global sources of liquidity innovations. This result contrasts with findings reported by Brockman et al. (2009) who show that local sources of commonality represent roughly 39% of the firm’s total commonality in liquidity, while global sources contribute around 19%.⁶ We also

⁶ This contrasting result could be due to the different methodologies followed by each study. To analyze the relative impact of the local and global components of commonality on the liquidity of individual firms, Brockman et al. (2009) perform univariate time series regressions. Here, our methodology is based on a VAR model, the main advantages of which are that all the variables in the system are treated as endogenous

observe that the “contribution from others” figures are quite similar across countries, with Switzerland being the largest receiver of liquidity spillovers. However, the “contribution to others” figures show interesting differences across countries. The largest transmitters are Germany, the U.K., France and Canada and, in fact, the “net contribution” row also shows them to be the largest transmitter countries.

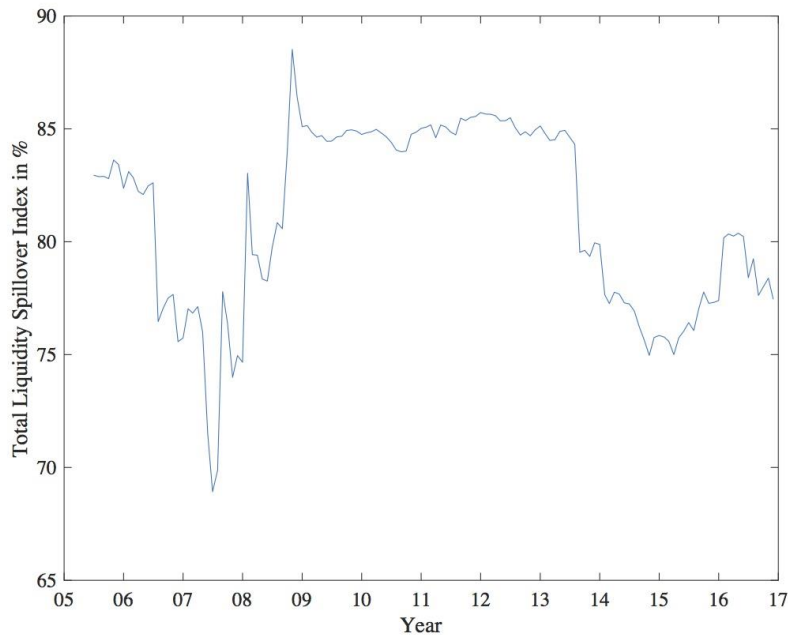
The above results point to a more cross-market oriented explanation of commonality in liquidity. From the demand-side perspective, this favors the hypothesis that large institutional investors, holding large-cap stocks from a variety of markets in their portfolio, can influence the systemic level of liquidity across markets by inducing high volume-related buy-sell trade imbalances (see Koch et al., 2016). From a supply-side perspective, a liquidity contagion effect from one market to another provides evidence that tightness of funding liquidity affects all securities across different markets (see Hameed et al., 2010). Finally, the total liquidity spillover (displayed in the bottom right-hand corner of Table 1) indicates that on average, across our entire sample, 80.96% of the total variance forecast errors come from cross-market liquidity spillovers, which gives an idea of the degree of cross-market connectedness. This result contrasts with the results reported by Diebold and Yilmaz (2009) in terms of volatility and return spillovers across different global equity markets. These authors conclude that, on average, around 40% of forecast error variance comes from cross-spillovers, as regards both returns and volatilities. Our results suggest that liquidity connectedness across national markets is much higher than that of returns and volatilities.

The static analysis provides a good characterization of the spillovers over the full sample period. However, as this study investigates commonality in liquidity over a period affected by extreme economic events, including the global financial crisis, it seems fairly unlikely that liquidity spillovers will not change over time. To assess the time-varying nature of commonality, we estimate the VAR using a 60-month rolling window and a 6-month forecasting predictive horizon for the underlying variance decomposition.⁷ From this, we obtain the total dynamic spillover index, which serves as our proxy for commonality in liquidity.

variables, which provides a systematic way to capture rich dynamics in multiple time series by way of the lag structure.

⁷ The results are robust to the use of a 10-month forecasting horizon.

Figure 2: Global commonality in liquidity



Note: Monthly total spillover index. Window length equals 60 months.

Figure 2 shows the total liquidity spillover index obtained from the rolling window estimation. It clearly highlights the changing dynamics over the sample period, with the level of commonality in liquidity mostly oscillating between 70 and 87%. The low peak at the beginning of 2008 can be associated with the liquidity constraints faced by Bear Stearns, while the collapse of Lehman Brothers in September 2008 is associated with an even steeper increase in commonality in illiquidity. This increment is consistent with the findings of Hameed et al. (2010), indicating that peaks in commonality in liquidity often result from large negative market returns and coincide with liquidity crises. Thus, the dynamics show that commonality in liquidity increases during episodes of market turmoil. Our empirical findings are coherent with the theoretical discussion in Brunnermeier and Pedersen (2009), where funding and market liquidity interact with each other, leading to higher margins and less capital-intensive trading positions in periods of crisis, which in turn leads to tight funding constraints and to changing levels in market-wide liquidity as funding liquidity diminishes.

Interestingly, we also observe that commonality is very persistent and that it remains at high levels even after market turmoil and funding tightness has passed. And even though the level of market-wide illiquidity in each country declined substantially after the effects of

the Lehman Brother collapse, depending on the respective market, to moderate levels (see Figure 1). This pattern is repeated during the European sovereign debt crisis, which followed on the heels of the global financial crisis. Investors seem to chase liquidity by rushing from periods of flight-to-quality to periods of flight-to-liquidity, running from the Eurozone bond markets back to equities which, in turn, keeps commonality high. Goyenko and Ukhov (2009), who analyze the dynamics between stock and bond market liquidity in the U.S. market, show that positive shocks to the level of illiquidity in the stock market reduce illiquidity in the bond market. Following a period of persistence in commonality in liquidity, a downward shift is observed at the end 2013, suggesting the normalization of conditions in both the bond and equity markets. The level of market commonality in the last few months of the sample is similar to that recorded in the months leading up to the global financial crisis.

4.3 Dynamics between global commonality in liquidity and global market volatility

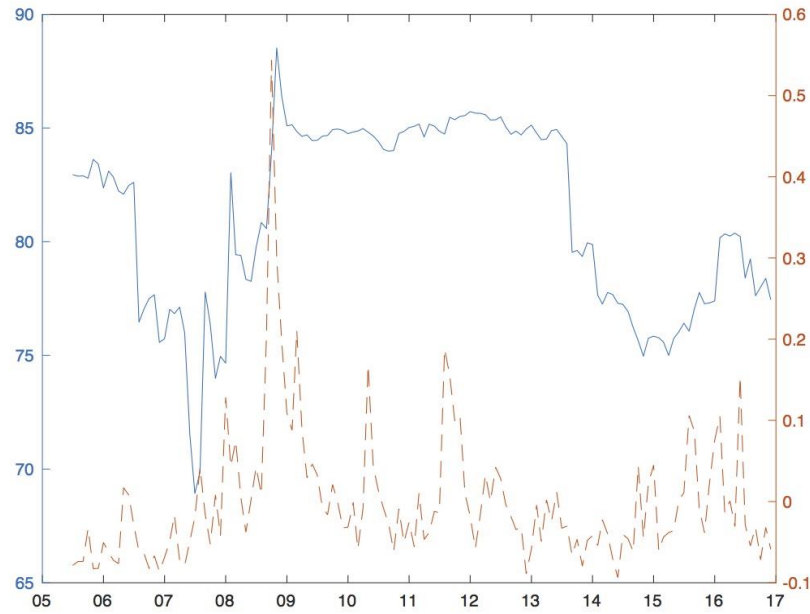
Figure 3 shows the joint dynamics of global commonality in liquidity and global market volatility. We observe an increase in both trends during the financial crisis, although the upward trend starts earlier in the case of commonality in liquidity. Remarkably, we find that while volatility returns to lower levels, albeit with sudden peaks, levels of commonality in liquidity remain persistent. To analyze the time-varying relationship between the two, we use the dynamic Granger causality test proposed by Hurn et al. (2016).

Our proxy for global market volatility is the first principal component factor of realized market volatilities in the nine stock markets.⁸ Figure 4 displays the dynamic Wald test statistics proposed by Hurn et al. (2016) for the detection of instability in the causal relationship between two time series, namely commonality in liquidity and market volatility. The sequence of t-statistics starts in May 2007, as the first 22 months are used as the minimum window size.⁹

⁸ As a robustness check, we have also calculated an equally weighted average volatility index for the same sampling countries, and the results (available upon request) were found to hold.

⁹ Our initial sample starts in July 2000. We use 60 months in our rolling window estimation to obtain the total dynamic liquidity spillover. Using this index as input into the dynamic Granger test, we then take an additional 22 months as the minimum window size to perform the dynamic causality test.

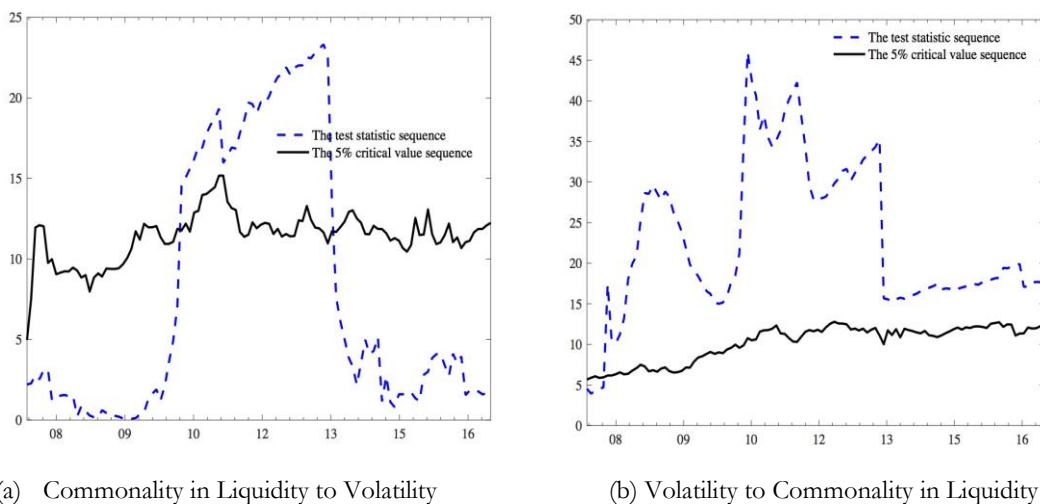
Figure 3. Global Commonality in Liquidity and Global Market Volatility



Note: This figure shows the index for global commonality in liquidity (solid line) and the proxy for global market volatility (dashed line).

We observe that global market volatility Granger-causes commonality in liquidity throughout the entire sample period. This is in line with the theoretical model developed by Brunnermeier and Pedersen (2009), in which high market volatility leads to an increase in commonality as a consequence of a reduction in the provision of liquidity available for all financial intermediaries. Conversely, and for the first time, we find that commonality in liquidity Granger-causes volatility only from late 2009 to 2013, that is, in the aftermaths of the global financial crisis and during the European sovereign debt crisis. These feedback effects between commonality in liquidity and volatility coincide with periods of high commonality in liquidity in global markets. This finding might be interpreted as evidence of the existence of adverse loop effects in which shocks to stock market liquidity endogenously cause stock market volatility and vice versa. Such a feedback effect sheds new light on the endogenous nature of financial shocks arising during episodes of crisis, which we show are aggravated by liquidity considerations.

Figure 4. Test statistic sequences of the time-varying Granger causality test between commonality in liquidity and volatility



Note: The lag selection is determined using the BIC. The sequences are calculated using a recursive rolling procedure from May 2007 to December 2016.

5. Conclusion

We document a dynamic relationship between global commonality in liquidity and global market volatility in a sample of nine stock markets, representing most of the world's stock market capitalization. Our results show that global commonality in liquidity and market volatility share a dynamic bi-directional relationship. Market volatility Granger-causes commonality in liquidity as a general rule (i.e. throughout the whole sample period), while commonality Granger-causes market volatility only during sub-periods of crises and their aftermaths. This latter relationship raises a warning about the presence of endogenously enhanced adverse loop effects between commonality and liquidity during crises, which are documented and measured here for the first time.

We also find that variation in market-wide liquidity depends predominantly on inter-market liquidity innovations, which reveals the relative strength of the propagation of liquidity shocks originating from foreign stock markets. Illiquidity shocks are indeed shown to propagate more strongly than volatility and return shocks extensively analyzed by the previous literature. These strong liquidity linkages provide support for both a demand-side explanation of commonality (i.e. correlated trading behavior and the increasing importance

of institutional investors in the market) and a supply-side explanation (i.e. funding constraints and liquidity spirals). The dynamics show that commonality in liquidity increases after large market downturns and peaks during episodes of market turmoil and funding tightness. We also observe that commonality is highly persistent and that it remains at high levels even after market turmoil has passed.

Our results should prove helpful for practitioners, as the relationships identified herein can usefully be taken into account in portfolio risk management. They might also be useful for policy makers as they highlight the high level of commonality across markets, which stresses the importance of designing an integrated policy framework to prevent common sources of liquidity shortage in global financial markets.

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Appendix

Table A1: Summary Statistics of Commonality in Liquidity

	Mean	Median	St.Dev.	Min	Max	Skewness	Kurtosis
<i>Pre-Financial Crisis (2000-2007)</i>							
US	1.740	1.430	0.671	0.907	3.866	0.894	2.998
CA	1.140	1.060	0.279	0.795	23.261	1.520	5.943
GER	1.830	1.790	0.628	0.894	3.521	0.675	2.673
ES	0.790	0.741	0.264	0.433	1.462	0.830	2.714
SWI	1.076	0.972	0.482	0.536	2.683	1.311	4.351
ITA	0.611	0.553	0.208	0.396	1.800	2.749	13.63
JPN	1.235	1.225	0.318	0.668	2.463	0.650	4.497
UK	1.180	1.130	0.362	0.706	2.246	1.032	3.551
FR	1.290	1.170	0.520	0.680	2.820	0.886	3.016
<i>Financial Crisis (2008-2009)</i>							
US	1.940	1.660	0.880	0.930	4.070	1.001	3.041
CA	1.590	1.250	0.900	0.820	5.310	2.322	9.390
GER	1.980	1.720	0.830	1.060	5.380	1.556	5.380
ES	1.200	1.040	0.490	0.660	2.871	1.448	5.210
SWI	1.290	1.080	0.570	0.620	3.035	1.210	3.914
ITA	1.030	0.920	0.440	0.450	2.383	1.110	3.920
JPN	1.630	1.497	0.675	0.880	4.580	2.368	10.57
UK	1.650	1.470	0.730	0.700	3.956	1.291	4.564
FR	1.540	1.300	0.660	0.710	3.560	1.100	3.892
<i>Post-Financial Crisis (2010-2016)</i>							
US	1.199	1.165	0.240	0.883	2.192	1.628	6.239
CA	1.004	0.964	0.259	0.628	1.959	1.195	4.629
GER	1.528	1.436	0.343	0.971	2.394	0.948	3.171
ES	1.057	0.983	0.300	0.601	2.103	1.325	4.930
SWI	0.856	0.824	0.227	0.447	1.692	1.128	4.837
ITA	1.145	1.082	0.362	0.578	2.690	1.375	6.028
JPN	1.254	1.166	0.359	0.687	2.247	1.259	4.269
UK	1.001	0.950	0.244	0.636	2.289	2.102	10.886
FR	1.090	1.030	0.290	0.660	1.950	1.257	4.231
<i>Full Sample (2000-2017)</i>							
US	1.547	1.296	0.654	0.883	4.069	1.656	5.451
CA	1.167	1.034	0.498	0.628	5.313	4.076	28.90
GER	1.730	1.546	0.600	0.894	4.821	1.605	6.649
ES	0.979	0.916	0.367	0.433	2.871	1.442	6.643
SWI	1.034	0.901	0.482	0.447	3.035	1.771	6.448
ITA	0.914	0.841	0.411	0.399	2.690	1.207	4.771
JPN	1.325	1.257	0.447	0.669	4.583	2.585	16.713
UK	1.190	1.061	0.475	0.636	3.956	2.344	10.878
FR	1.250	1.100	0.500	0.660	3.560	1.504	5.613

Note: This table reports summary statistics for the liquidity measure proposed by Abdi and Ranaldo (2017). Our dataset spans from July 2000 to December 2016.

The logo for UBIREA, featuring the text "UBIREA" in a bold, sans-serif font. The "UB" is in a light blue color, and "IREA" is in a darker blue. The logo is set against a white background that is part of a larger blue graphic element.

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